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USE OF LIFE-TEST DATA ANALYSIS METHODOLOGY FOR ANALYZING UNDESIRABLE HABITUAL BEHAVIOR.

by

10 Nancy R. Mann

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USE OF LIFE-TEST DATA ANALYSIS METHODOLOGY FOR ANALYZING UNDESIRABLE HABITUAL BEHAVIOR*

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This paper concerns statistical methodology used in the analysis of data consisting of failure times of samples of hardware operated under equivalent conditions to the intended usage of the hardware. It is suggested that this methodology can be applied to available sets of longitudinal data of individuals engaging in habitual behavior deemed to be undesirable. The longitudinal data, which might be available from several sources, consist of intervals beginning with time of remission of the habitual behavior and ending with time of relapse, or return to the behavior.

The behavior of interest might be of various types; for example, eating of forbidden foods by a person on a prescribed diet, a drug addict's use of drugs, an alcoholic's drinking, smoking for a person who wants to terminate the habit, and recurring incidences of infirmities such as fatigue (including battle fatigue), headaches, or colds. With one exception, the examples used in the following to demonstrate the adaptation of the subject methodology for analysis of times between periods of recurring undesirable behavior concern problem drinking and alcoholism.

Armor, *et al.* [1], discuss, in some detail, results of many studies relating to client factors in alcoholism treatment outcome. They conclude that "social stability in the form of steady employment, residency, and familial relationships" is "a positive prognostic factor in both inpatient and outpatient treatment." On the other hand, results relating treatment success with certain other socio-economic variables, such as age and sex, or with psychological attributes have been found, according to Armor, *et al.*, to be sometimes contradictory. Thus, it has been difficult to predict, for example, which individuals in a population in which all have steady employment, residency and familial relationships, might be most likely to exhibit a treatment effect. And, in fact, it is not simple to define a treatment effect when dealing with alcoholism, addiction to other drugs or, in fact, any sort of undesirable habitual activity.

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*Written while the author was at The George Washington University on leave of absence from the Science Center, Rockwell International.

Part of the difficulty here may be that comparative studies of treatment of alcohol and drug addiction and other sorts of unwanted habitual behavior tend to be conducted by medical and psychotherapeutic personnel exclusively. Thus, innovative statistical techniques that might bring new insights have rarely been used. Another aspect of the difficulty may be that study of behavior has been concentrated on behavior while engaging in the behavior or has been concerned with determining why individuals relapse. Information that could be provided by considering data about intervals of abstinence has been largely overlooked. For example, we have found that it is very useful to collect or use available longitudinal data on lengths of times of abstinence for individual alcoholics and drug users much as one might collect or use life-test data on a sample of hardware.

By analysis [2] of failure data generated by life tests, i.e., number in a sample failing by a specified time and/or the actual times of the failues, one can estimate the probability of survival until a specified time of the type of hardware subjected to test, under conditions typical of the test. One can also determine if items manufactured by different methods or subjected to different treatments are significantly different with respect to probability of survival. By analysis of the actual failure times of the sample items, it is also possible to estimate whether the hardware of interest is subject to wearout, simply experiencing random catastrophic failure, or if it is in a "wearin" situation in which failure is caused early by manufacturing errors such as loose connections, improper solders, etc. that may or may not be present in a particular item.

If the failure times of the sample items tend to be grouped close together, then there is indication of wearout or increasing failure rate.* A wearin situation with decreasing failure rate* is indicated when failure occurs either very early because of manufacturing defects or after a rather long period of operation. Simple catastrophic failure with constant failure rate gives a pattern of sample failure times that is between these two extremes.

If failure occurs in the subject hardware because of a weakest link, e.g., a severest flaw or largest crack, and there are a great many such flaws or cracks, then one might expect the failure times to be distributed according to the Weibull distribution, an asymptotic distribution of extremes that is limited on the left. For a two-parameter Weibull model, the probability of failure before time t is given by

---

* Failure rate here is defined as the probability of failure of an item at time t, given that the item has survived until time t.

$$F(t) = \begin{cases} 1 - \exp(-\alpha t^{\beta}), & t > 0 \\ 0, & \text{otherwise}; \ \alpha, \beta > 0 \end{cases} \quad (1)$$

When the Weibull distribution applies, then it is possible to estimate probability of survival and whether or not two or more populations are really operationally different by estimating the Weibull distribution parameters. One can also estimate whether there is wearout, wearin, or constant failure rate by estimating these parameters, since wearout is associated with a shape parameter (β) greater than one, wearin implies a β less than one, and constant failure rate is identified with a β of one. Examples will be given subsequently in the context of habitual behavior relating to substance abuse. By these examples it will be shown how collection of data relating to lengths of times of abstinence can offer new insight into the potential of the addict for realizing a treatment effect. Such analysis also helps to reveal how one may define a treatment effect and what may have produced such effects, if any, in a given individual in the past. This allows the patient to provide a baseline and to be used as his or her own control.

APPLICATION OF LIFE-TEST DATA ANALYSIS TO ALCOHOLIC FAILURE DATA

Life-test data analysis, to be most effective, requires the use of times to failure for the hardware subjected to life test. In the present context it has been found that detoxification provides a time that one may fruitfully define as the initiation of a life test and the beginning of a "time to failure." Thus, a single individual will generate successive times to failure in a manner described in the following, much as will a sample of hardware, each of whose sample items is subjected to test serially upon failure of the item tested just before it in serial order. That this is an orderly or natural means of defining a life-test period is attested to by the fact that resulting data generated by a single individual tend to belong to a classical distribution of times to failure.

Detoxification is used loosely in the following as any time an addict abstains from ingestion of the substance to which he or she is addicted long enough to eliminate the drug and its immediate toxic effects from his or her body and brain. Detoxification in this sense may result from inpatient or outpatient treatment at a treatment center or a hospital, may be self-induced as a result of social pressure of family members, a friend or an employer, or temporary unavailability of the substance, or simply from a decision on the part of the addict or drug abuser to give up his or her habit because of its deleterious effects.

We will define number of days to failure as the number of days from detoxification until resumption of use leading to a subsequent detoxification. When utilizing historical hospitalization data coming from the armed forces, we define time-to-failure as the number of days between hospitalizations resulting from alcohol or other drug use. In general, however, it is better to eliminate time of using drugs before a next detoxification from consideration, since length of time using after resumption of use may be affected by various extraneous factors, including form or strength of drug.

Data applying to times between hospitalizations for alcoholism at Walter Reed U.S. Army Hospital has been analyzed and some results are shown in Figures 3 through 5. In order to describe the techniques employed in analyzing the Walter Reed data, we first discuss a single illustrative case.

The times to failure shown in Table 1 cover a period of nearly three years in the life of one alcoholic subject. At the initiation of the periods of abstinence marked with an *H*, the subject was hospitalized because of alcohol induced illness or because he was unable to stop drinking on his own. On the other occasions, he simply stopped drinking, usually because of family coercion. These data were obtained from the wife of this individual. The husband, when drinking, stays intoxicated essentially all waking hours. If he drinks distilled spirits he can maintain this drinking schedule for no more than two or three weeks before requiring detoxification. Drinking beer, he can remain drunk daily for several months at a time. The times of abstinence shown in Table 1 are associated with both types of drinking. Following the fifth failure, the subject was exposed weekly to psychological counselling which continued until just after the eighth failure.

A test for lack of randomness applied to the data in Table 1 seems to indicate that the subject exhibited no tendency toward longer or shorter periods of abstinence over the years represented. That is, no "learning" appeared to manifest itself.

Since the times to failure seem to be randomly distributed throughout the nearly three year period, one might hypothesize that they would be distributed according to the exponential law, a special case of the Weibull distribution. In such a case, when the subject is engaging in a period of abstinence, return to drinking occurs because of a random event generated by what is called a "homogeneous Poisson process." For exponentially distributed failure times, failure rate is constant and the Weibull shape parameter has a value of one.

Table 1

Number of Days Until Failure
(H indicates hospitalized detoxification)

	In order of occurrence	In increasing order	Natural logarithms
1	58	14 H	2.6391
2	14 H	27	3.2958
3	90	38	3.6376
4	67 H	42	3.7377
5	245 H	58	4.0604
6	42	67 H	4.2046
7	27	90	4.4998
8	38	245 H	5.5013

To investigate this possibility, one can plot [2] the failure-time data shown in Table 1 on Weibull probability paper to see if the data tend to be from a Weibull population and thus distributed about a straight line, and if the line has a slope of one (since the slope of the line in the plot gives an estimate of the Weibull shape parameter).

To make the plot we first order the data according to increasing size, as in the next-to-last column of Table 1. We then plot a prescribed function of (i-0.5)/n (where n is sample size) versus the logarithm of the *ith* smallest failure time. Here (i-0.5)/n is used to estimate the proportion ($P(t_i)$) in the population that has failed by time t_i. The linear relationship estimated in Figure 1 between $\ell n(t_i)$ and $\ell n \ell n \frac{1}{1-P(t_i)}$ results from applying a logarithmic transformation twice to the Weibull cumulative distribution function given by (1) For more details on Weibull plots, see [2], pp. 214-17).

The plot shown in Figure 1 appears to reflect the fact that "something different" happened as a result of, or following, the fifth detoxification (which the subject experienced as a private patient in an ordinary hospital). The data set represented by the seven shortest failure times and other data sets collected (including the majority of the Walter Reed cases) are fit well by a Weibull model. The "goodness-of-fit" test of Mann, Scheuer, and Fertig [3] does not reject (even at high significance levels) the hypothesis that the seven shortest failure times in Table 1 are from a single Weibull distribution. This test involves comparing the first half of the differences of the ordered logarithms of times-to-failure (as shown in the last column of Table 1) with the second half.

It is possible then to use the Weibull model to test whether or not the discrepency between the eight month time-to-failure and the central tendency of the other seven observations is larger than to be anticipated when one considers the variability of the data. An approximate outlier test, which is an analogue of the prediction interval technique described on pages 254-6 of Mann, Schafer, and Singpurwalla [2], rejects the hypothesis that the largest observation plotted in Figure 1 is the largest of a Weibull sample of size 8. An exact test and a test for treatment effect [4] have been developed and are in the process of being implemented by construction of tables. In the outlier test, the difference between the logarithm of the longest time-to-failure and that of the next longest is compared with an unbiased linear estimate of β^{-1}, a scale parameter of the distribution of the logarithm of failure time.

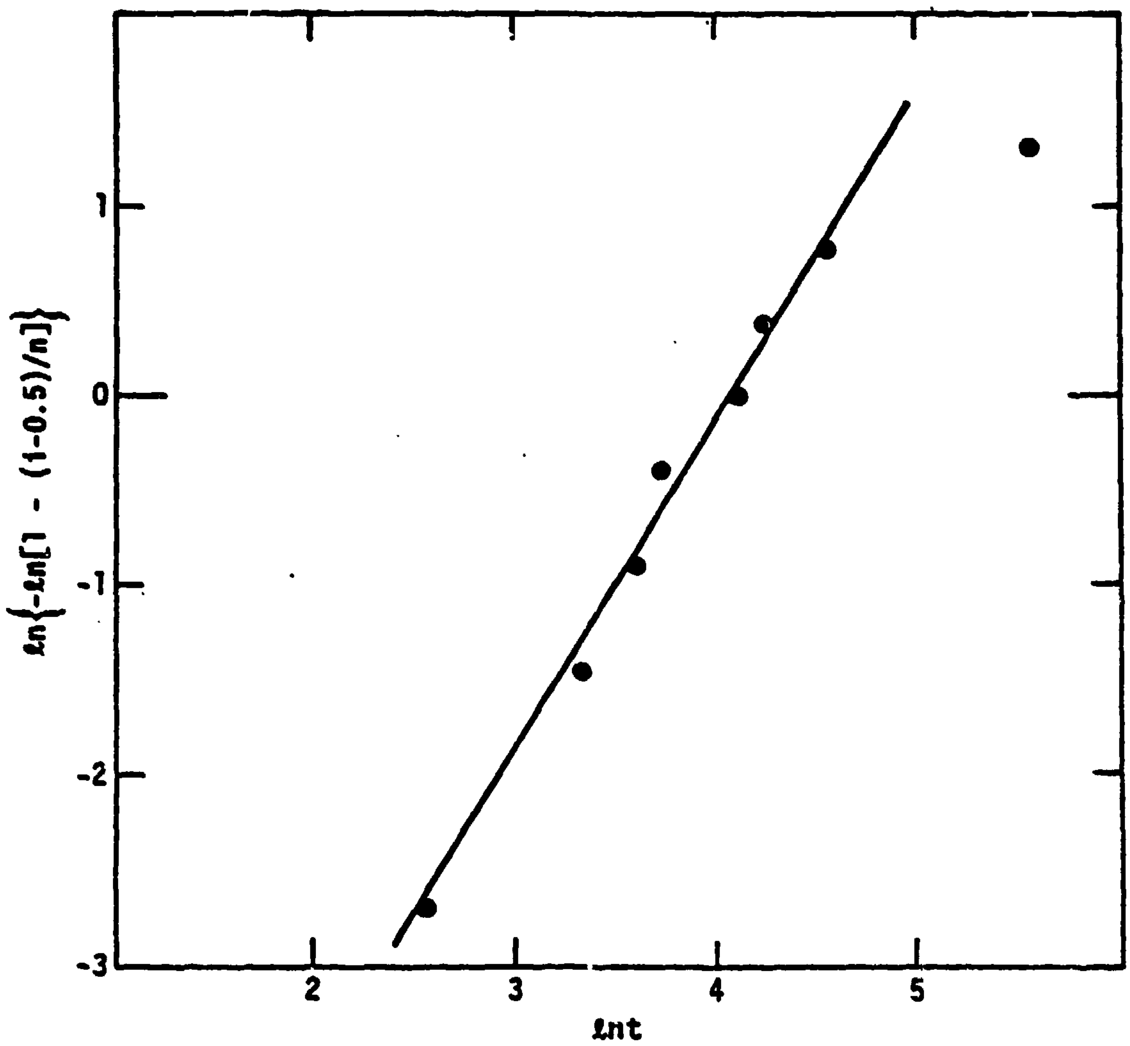


Fig. 1 Weibull probability plot of number of days from detoxificatiou until failure (data from Table 1)

Estimation of a Weibull shape parameter (see Mann [5]) for the underlying distribution of the seven times to failure that range from 14 to 90 days yields a value of about two. This suggests (since the value is greater than one) that the subject, during these periods, experienced increasing failure rate or wearout. Nonparametric estimation of the failure rate by Barlow's [6] *total time on test* plot also indicates wearout. Thus, staying sober on any particular day during a given period of sobriety appears to have become more and more difficult with time for this subject. (A 90 percent lower confidence bound [2] on the Weibull shape parameter is a value slightly greater than one.)

A plot of the times to failure that followed hospitalized detoxification (indicated by the letter *H* in Table 1), along with an eight-year period of abstinence that immediately preceded the time period reflected by these data, is given in Figure 2. This data set, as a group, exhibits behavior that is reminiscent of data obtained as a result of failure behavior of electronic systems. The wearouts reflected by the two shortest failure times in the data set are analogous in this context to early wearouts in electronic equipment caused by loose connections, faulty components, etc.

One tends to observe a large discrepancy in time-to-failure between detoxifications in which early wearout is exhibited and those in which there is elimination of early wearout modalities (a treatment effect takes place). In other words, if the subject whose failure data are being analyzed abstains from alcohol after hospitalization for longer than two or three months, one might predict that there is a high probability that he will abstain nearly a year, or considerably longer than one year.

This data set is typical of data from a distribution that exhibits "wearin" or decreasing failure rate. The estimate obtained [5] for the Weibull shape parameter is about 0.5 and an upper 95 percent confidence bound is 0.76. A rough estimate can be obtained as the slope of the line plotted in Figure 2. If the true shape parameter is less than one, which seems likely, the longer the subject stays sober following a hospitalization, the higher the probability of his staying sober on any given day in a fairly constant environment. Or, the more severe the temptation required to motivate him to return to drinking. Thus, whether we consider the 14-day and 67-day failure times following hospitalization as belonging to an increasing or decreasing failure-rate population depends on whether or not we consider them to be possible candidates for exhibiting treatment effects, i.e., part of a strictly treatment-associated population, or not.

By collecting the data and performing a statistical analysis we have learned the following about the drinking patterns of the subject.

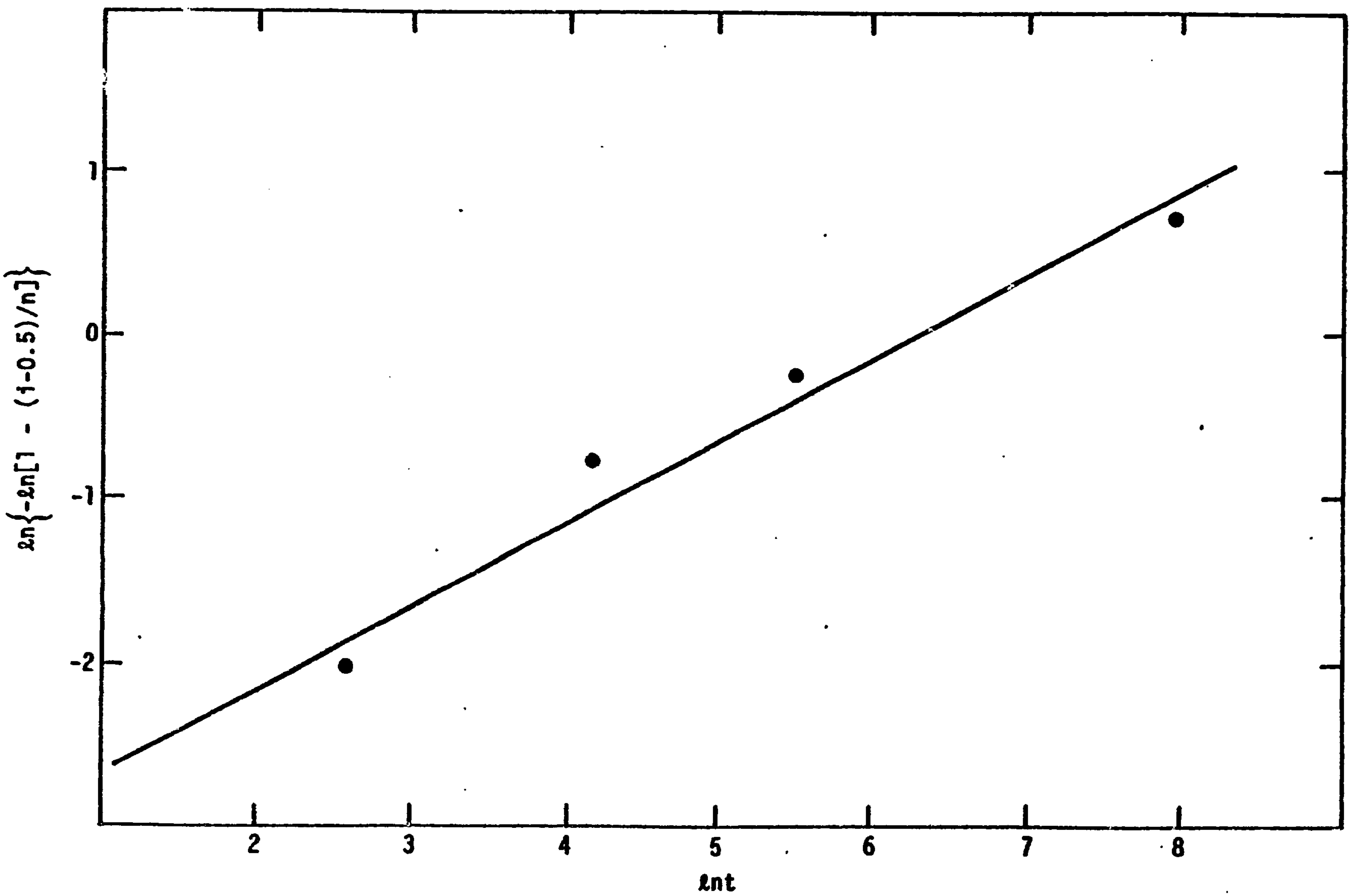


Fig. 2 Weibull probability plot of number of days from hospitalization until failure

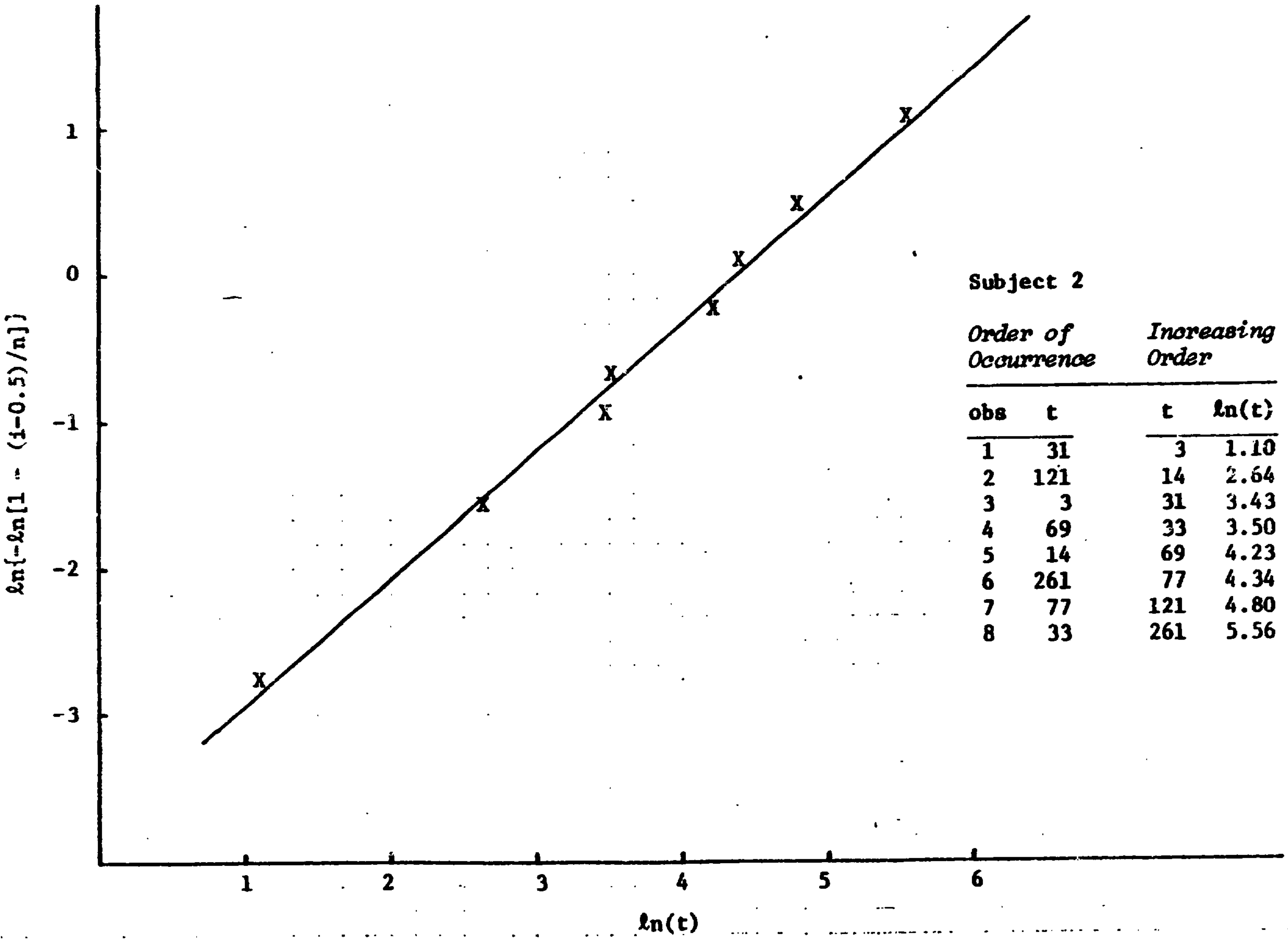
(1) On his own, or if not experiencing a treatment effect, this person appears to be subject to wearout on the average of about two months after beginning each attempt to stay sober. Moreover, no "learning effect" is evidenced over time; i.e., the failure times appear to be randomly distributed throughout the time period investigated. These facts, along with the fact that the times to failure in which no treatment effect is experienced behave like independent sample observations from a single distribution, suggest that each detoxification of this person begins a process that is, in some sense, independent of preceding events.

(2) A treatment effect seems to be associated with a time-to-failure that can be shown to be an outlier from a distribution of failure times that is characterized by nondecreasing failure rate, or with the extreme sample points from a decreasing failure rate distribution. Thus, it is possible to define a treatment effect by using the patient as his or her own control, rather than comparing with a fixed standard.

(3) For this individual, a treatment effect appears to have occurred only during, or following, a hospitalized detoxification, i.e., never following a self-induced detoxification. On the other hand, hospitalization did not guarantee a treatment effect. It is interesting that the eight-year period of sobriety followed a detoxification in an alcoholic hospital, the first few hours of which were spent in the company of a member of Alcoholics Anonymous.

(4) Finally, this individual seems to be one with relatively high potential for experiencing a treatment effect, having apparently experienced at least two such in the past.

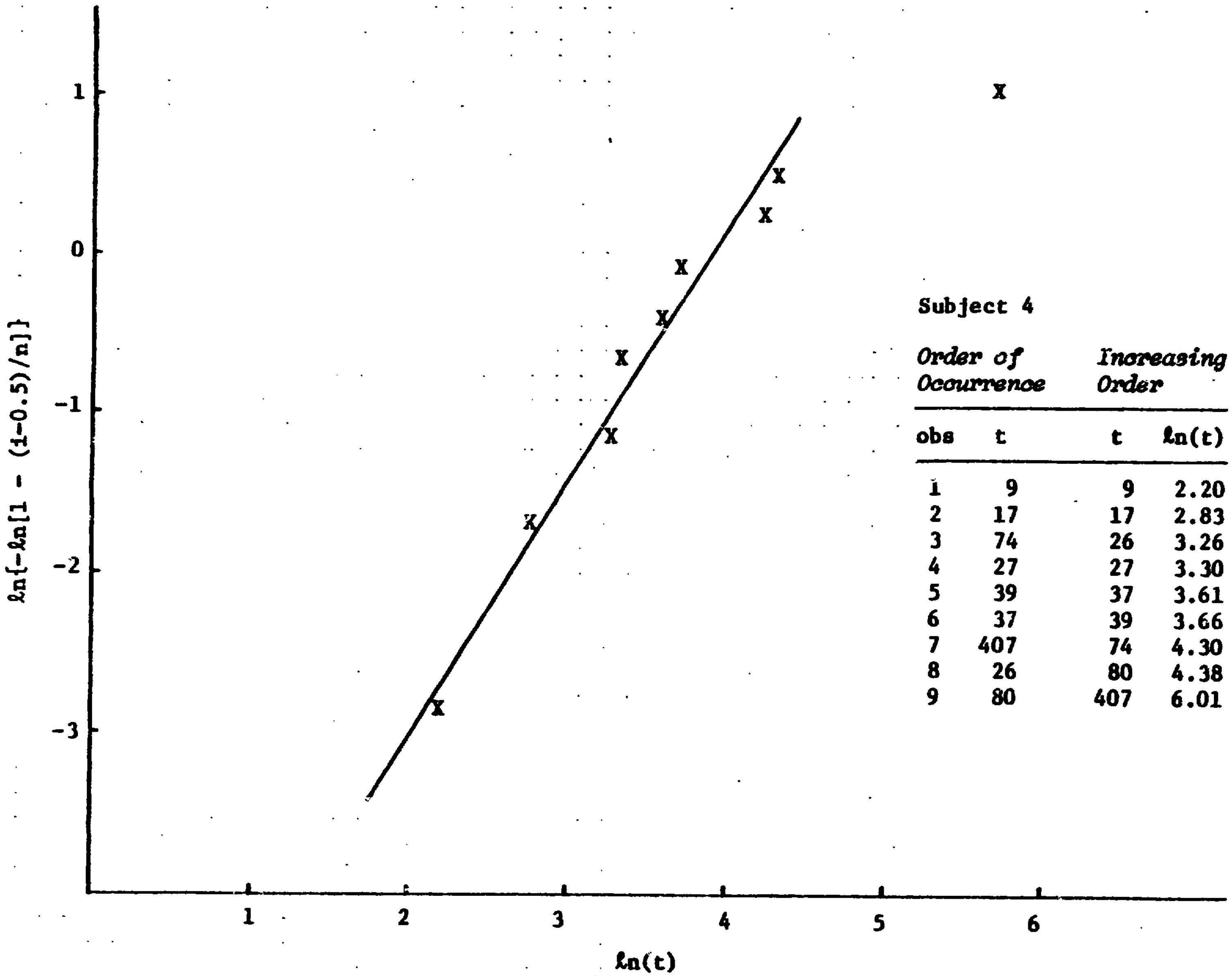
The data sets shown in Figures 3 through 5 relating to times between alcoholism hospitalization of U.S. Army personnel at Walter Reed Army Hospital [7] all yield good linear plots on Weibull probability paper, except that two exhibit apparent outliers. Again we find no trend toward longer periods of sobriety over time. And this appears to be true for all Walter Reed data sets, even though an alcoholism treatment program was in effect there at the time the data were generated. Some of the hospitalizations were in conjunction with diagnoses of serious physical debilitations. However, none of the hospitalizations associated



Subject 2

Order of Occurrence obs	t	*Increasing Order* t	ℓn(t)
1	31	3	1.10
2	121	14	2.64
3	3	31	3.43
4	69	33	3.50
5	14	69	4.23
6	261	77	4.34
7	77	121	4.80
8	33	261	5.56

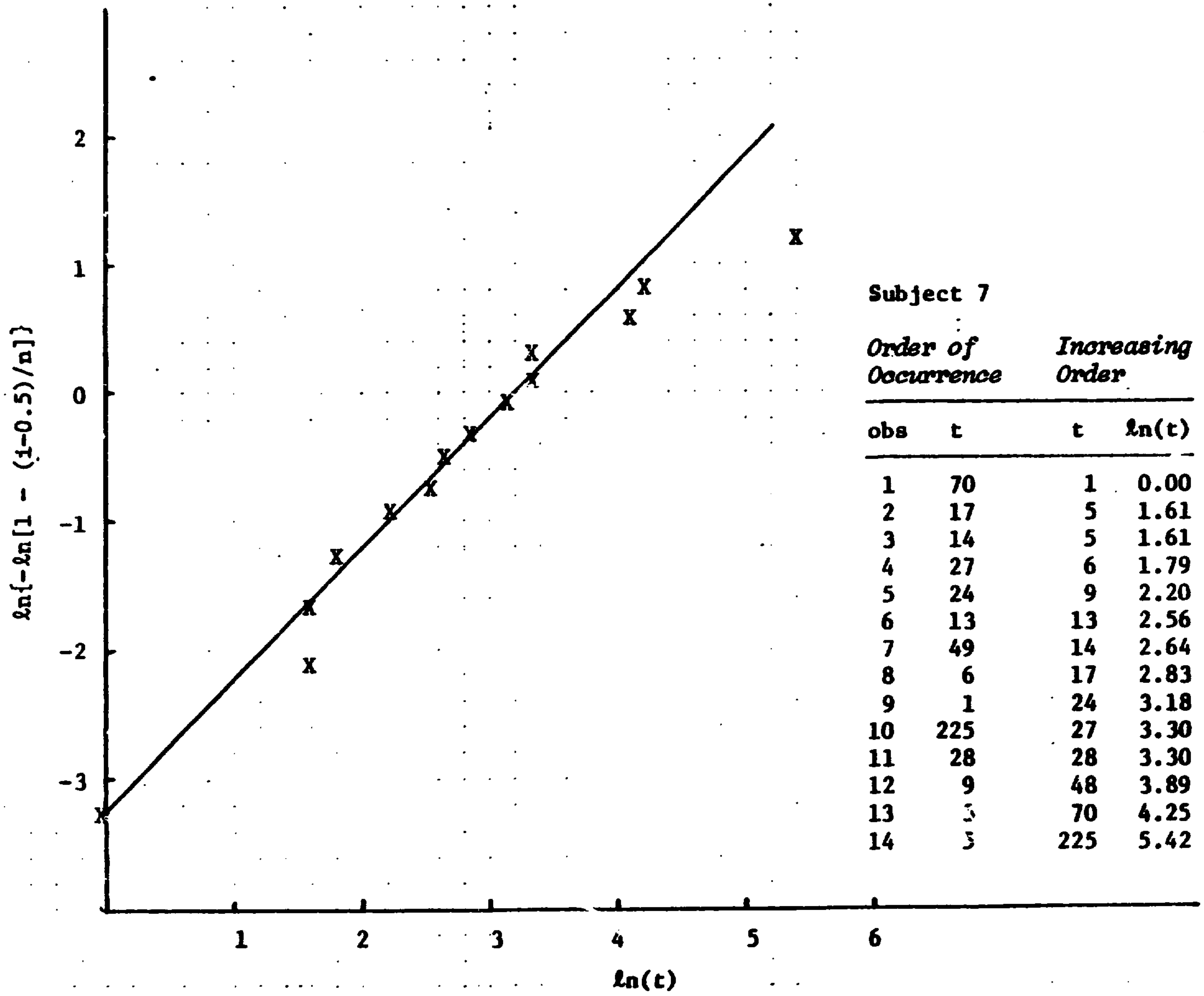
Fig. 3 Weibull probability plot of days between alcoholism hospitalizations



Subject 4

Order of Occurrence		*Increasing Order*	
obs	t	t	ℓn(t)
1	9	9	2.20
2	17	17	2.83
3	74	26	3.26
4	27	27	3.30
5	39	37	3.61
6	37	39	3.66
7	407	74	4.30
8	26	80	4.38
9	80	407	6.01

Fig. 4 Weibull probability plot of days between alcoholism hospitalizations



Subject 7

Order of Occurrence		*Increasing Order*	
obs	t	t	ℓn(t)
1	70	1	0.00
2	17	5	1.61
3	14	5	1.61
4	27	6	1.79
5	24	9	2.20
6	13	13	2.56
7	49	14	2.64
8	6	17	2.83
9	1	24	3.18
10	225	27	3.30
11	28	28	3.30
12	9	48	3.89
13	5	70	4.25
14	5	225	5.42

Fig. 5 Weibull probability plot of days between alcoholism hospitalizations

with serious illnesses initiated an unusually long period of sobriety. On the other hand, almost all of the clear outliers marked by unusually long periods of sobriety began following a traumatic accident resulting in an injury. This is a result, whatever its implications, that could not be discovered by analysis solely of drinking behavior.

In the three plots shown, one sees results of behavior that appears to be exponentially distributed or characterized by wearout (slopes of one or greater). That is to say, none of the behavior patterns of these three subjects appears to have a distribution that one would associate with a treatment program that makes an impact and as often as not achieves a treatment effect (see Figure 2).

We consider now Subject 2, whose number of days between alcoholic hospitalizations are shown in Figure 3, and who exhibits behavior that is essentially exponential, seemingly indicating no particular attempt to exert self-control. The same exponential pattern seems to be shown by Subject 7 (see Figure 5), except that observation number 10, 225 days, appears not to belong to the population associated with the other 13 times between hospitalizations. The 225-day period began after a hospitalization resulting from an accident in which he fell down a flight of stairs.

Subject 4, whose data are shown in Figure 2, also appears to have generated a single inordinately long period between alcoholism hospitalizations. This long period followed a hospitalization that began after a traumatic accident in which his nose was broken. The remaining data of Subject 4, however, behaves like sample data from a single population of items that are subject to wearout.

None of the information inferred from the failure-time data analysis could be extracted from the extensive admissions data presently being collected on standard U. S. Government Client Intake Forms [1] at alcoholism treatment centers throughout the United States. Not only is it possible to learn a great deal about a particular patient by the failure data analysis, but also one can begin to define operationally results of attempts to thwart the addiction and habituation process is in a way that lends new insights. One might infer, for example, on the basis of additional evidence, that attempts of many, or possibly most, drug addicts to exert self-control result in a wearing out of good intentions, the average time and rate of which will tend to vary with the individual, but may be fixed for classes of individuals. That exertion of self-control, by itself, is relatively ineffective in dealing with addictions and psychological fixations is accepted by many investigators, but rejected or not considered by others [8]. The wearing out process is not, however, one that is generally discussed by researchers in the fields of alcoholism and other drug addictions.

Another hypothesis that might be tested further by means of this methodology is that physical trauma (or simulation of physical trauma) at the time of initiation of detoxification tends to motivate the detoxified subject or to render him or her more subject to motivation to abstain for a period longer that would ordinarily be expected. Other potentially promising aspects of this type of analysis are the characterization of individuals engaging in a particular form of undesirable habitual behavior and the identification of the form of individual and collective failure-time distributions. Identification of failure-time distribution can possibly lend insight into the physiological and psychological mechanisms involved in addiction and habituation processes.

The Weibull model provides an excellent fit, not only to several data sets collected individually, but also in most cases for data obtained from Walter Reed Hospital. This suggests that there is an extreme-value phenomenon that triggers return to uncontrolled drinking after detoxification, since the Weibull is a classical extreme-value distribution. It may be, as suggested by Gunderson [9], that the subject succumbs to whatever is the "strongest temptation" for that person at the moment of succumbing. Because both the environment and the physiological and emotional states of the individual are in continuous flux, the number of temptation states is literally infinite. Thus the requirement necessary for an *asymptotic* distribution is satisfied.

The technique of analyzing time between events has been applied to days between discovery of strangulation victims* of the Los Angeles area "Hillside Strangler." The "Strangler" data (see Figure 6) are typical of exponentially distributed failure times generated by a homogeneous Poisson process and thus seem to indicate a lack of attempt to control the strangulation "habit" during the interval applying to the data. This is an inference in keeping with published analyses of the personality of this individual by several psychologists.

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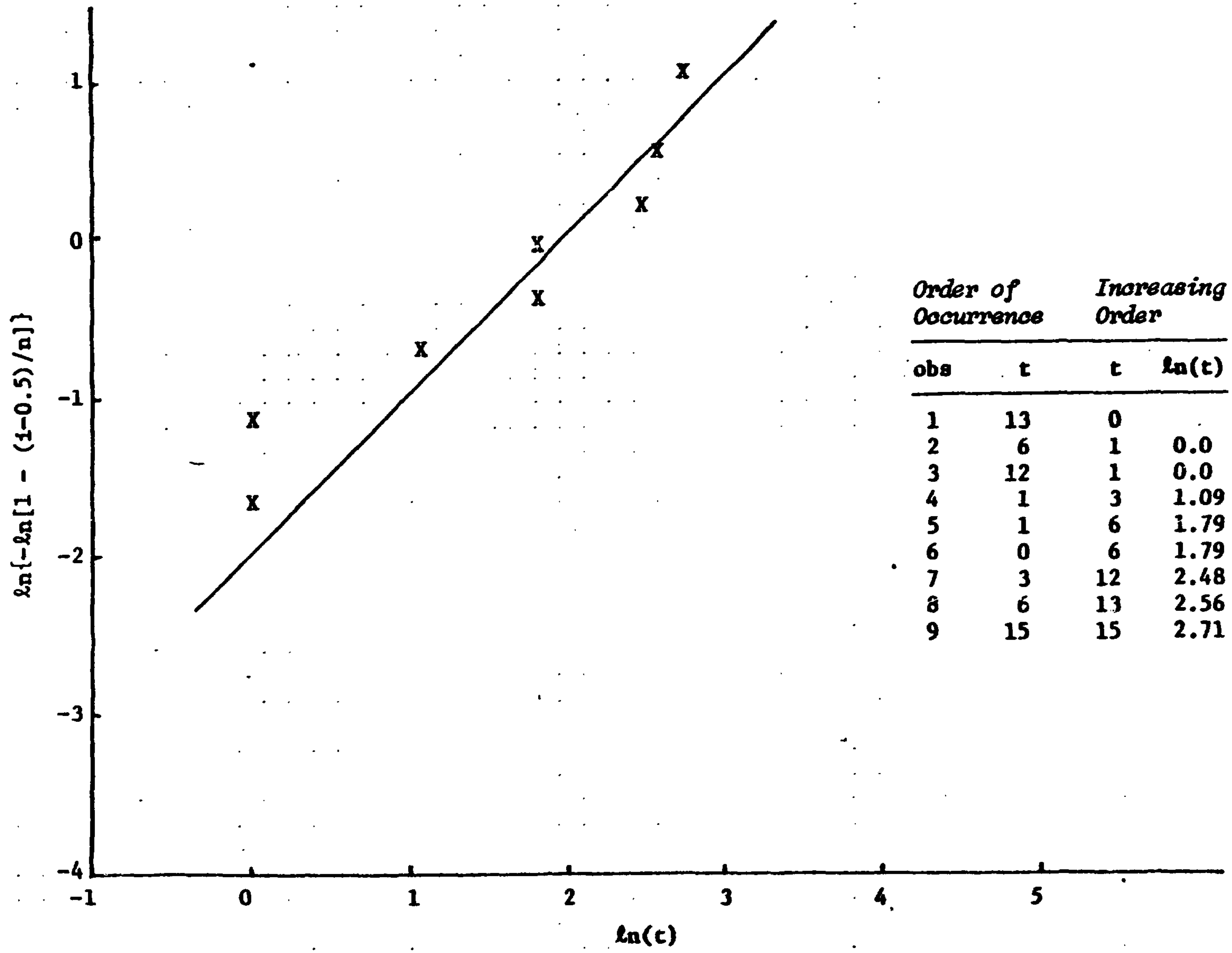
* The victims were left in spots where they could be readily discovered by passers-by, so the data are not contaminated by a delay factor relating to a search. Since the data are rounded to whole days, however, the very small intervals should probably be averaged.



Order of Occurrence		Increasing Order	
obs	t	t	ℓn(t)
1	13	0	
2	6	1	0.0
3	12	1	0.0
4	1	3	1.09
5	1	6	1.79
6	0	6	1.79
7	3	12	2.48
8	6	13	2.56
9	15	15	2.71

Fig. 6 Weibull probability plot of days between discovery of strangulation victims

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